An Overview of ANN Applications in the Power Industry

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Abstract

The paper presents a survey of the development and experience with artificial neural net (ANN) applications in the area of electric power systems, with emphasis on those ANN systems already operational in the power system utilities.

In the first chapter, the organization of the electric power transmission system is briefly reviewed, the specific constraints in the operation of this system are discussed. The second chapter attempts to identify the motivation for investigating artificial neural net applications in this context.

In the third chapter, an assessment of the current state of the art of this research and development activity is presented. It reports on a world wide experience from more than 240 different published research and industrial projects using ANN in the area of load forecasting, alarm processing, fault detection, component fault diagnosis, static and dynamic security analysis, system planning and operation planning.

A condensed reference list of some ANN projects is provided in order to point tl e audience to some more detailed information in the different application areas.

Keywords: *Artificial Neural Networks, Electric Power System Planning, Analysis, Diagnosis, Operation and Control*

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Chapter 1 Introduction to Electric Power Systems

1.1 Technical Aspects of Power System Operation

Electric power systems represent complex systems involving many electrical components whose operation has to be planned, analyzed, monitored and controlled. Electric power is transmitted from power sources, called *generation plants* or *generators* to power end users called *loads* which are connected through a *transmission* and *distribution* network. The time-scale of tasks in electric power systems extends from long term *expansion planning* years ahead through *operational planning* with constraints in the order of minutes to days, power system *analysis*, *diagnosis* and *operation* in the order of minutes to hours, to *monitoring* and *control* where remedial actions have to be executed within of tens of milliseconds.

In a power system, the generation is distributed over several power plants, and the load is situated at discrete locations in the system. The interconnection of power systems offers the economical advantage of exploiting the diversity of thermal, nuclear and hydraulic generation, by energy exchanges between partners. Although the power system *controlled* by one utility may be small (in the order of 100 busses and lines), the power system to be *analyzed* for operation and planning usually comprises the majority of interconnected system (up to 1000 busses and lines).

1.2 Power System Planning

Expansion System Planning

System *expansion planning* deals with the installation of new power system components like lines or transformer. Long-term load forecasting is needed in order to ensure the safe, reliable and economical operation of the system.

Operation Planning

Operation planning includes *generator maintenance scheduling* of power generation plants, *unit commitment*, *economic load dispatch*. and *short-term load forecasting*. Optimal generator maintenance scheduling has to be solved for a time period of 1-2 years. Unit commitment selects the optimal schedule of generators in order to minimize the total operating cost subject to constraints on power balance, spinning IL'serve, generation limits and minimum up/down time. In general, unit commitment is solved for a time horizon of 24 to 168 hours and it provides basic data for daily operation planning, that is, economic load dispatch (ELD). ELD determines the optimal generation for each generator in order to minimize the total fuel costs subject to equality constraints on power balance and inequality constraints on generation rate changes and line flows. The ELD command is usually dispatched to each unit every 3 to 5 minutes. [CIGRE, 1005]."

The majority of planning tasks present mixed-integer optimization problems dealing with the minimization 01' transfer losses, efficient power generation and low-cost system operation. The complexity of these problems dramatically increases with the number of units due to their combinatorial nature.

Load Forecasting

Short-term load forecasting (LF) deals with the prediction of daily peak loads, hourly loads and 5 minutes-ahead load demands. Load demands are of stochastic nature and depend heavily on the load nature (residential, commercial and industrial), on the meteorological situation (temperature, climate, moisture), and on the geographical situation and social habits, (urban, rural, type of day, working hours, use of television, air conditioning, main meal times, etc.) The LF task is modeled as a combination of a classification problem, (load type, day type) and a time-series prediction problem (peak load, hourly load). However despite existing statistical approaches, the majority of utilities still rely on the intuitive forecast done by a human operator.

1.3 Power System Operation

The principal task of power system *operation* is to deliver the power requested by the customers, without exceeding acceptable voltage, line load and frequency limits. This task has to be solved in real time and in a safe, reliable, and economical manner.

Static and Dynamic Security Assessment

It is an accepted standard that a modern power system should remain within safe operating limits for any single outage of a line, a transformer or another component. Power system *static security assessment* is concerned with possible violation of voltage, bus power and line load constraints while the system is operating in steady state. Time constraints 1(M remedial actions are usually in the order of 10-30 minutes. *Dynamic security assessment* analyses possible frequency violations and loss of voltage stability in the case of transient events like unforeseen outages and short-circuits. Depending on the nature of the problem, remedial actions have to be taken within milliseconds to minutes. Although efficient power system simulators exist, real-time power system security assessment is limited by the combinatorial nature of its problems. Exhaustive simulation of multiple outages and dynamic, time-dependent, security assessment can not yet be solved in real-time.

Alarm Processing and Fault Location

In case of a fault, automatic relay operation, breaker opening and reclosure will issue a series of binary alarms and analog measurements which arrive at the power system control center in not-necessarily-chronological order. *Alarm processing* attempts to reestablish the sequence of events leading to the failure of a component. *Fault location* deals with the identification and location of the faulty component. Because of the non-chronological alarm sequence, measurement errors and malfunctioning of relays, this task has to deal with the evaluation of a considerable number of hypotheses. The measurements available for fault section estimation can be evaluated with pattern recognition techniques.

Component Fault Diagnosis

Once the faulty component is determined *component fault diagnosis* attempts to identify the fault type. The identification of incipient faults in components due to external events (falling trees, animals) or internal failure (over heating, material fatigue) is formulated as a pattern recognition and classification task. Modern power system components like transformers or gas insulated substations are monitored by sensors in order to predict and prevent developing faults, thus limiting the damage, repair costs, outage time, and danger to the environment.

1.4 Power System Identification and Control

Power System Identification

Power system identification is defined as the process of determining a model of a dynamic system using measured data. *State estimation* and *dynamic load modeling* are examples of this area. They serve as input data for power system analysis and control tools.

Power System Control

Automatic power system control (PSC) is executed locally at the generator level in order to keep variables like generator terminal voltage and frequency within safe operating limits. Controlled parameters include field excitation current and turbine valve settings which effect the power output. PSC uses system identification, signal processing, filtering and prediction techniques. PSC is executed as closed loop control without human intervention within a time frame of milliseconds.

Corrective switching is concerned with decisions and actions to be taken in order to bring the power system from an statically or dynamically unsecure state back to a normal state. The time frame for these type of control actions is in the order of minutes. Actions are performed by a human operator.

1.5 Summary of Power System Tasks

Figure 1 summarizes principal tasks of power system planning, operation and control. Real-time measurements from the operating power system are stored in a data base. The state estimator then adjusts bad and missing data. Based on the estimated value the mathematical model of the power system is established. Assessing the potential damage of simulated equipment outages, the security level of the system is determined. Automatic control is executed for bus voltage and frequency deviations. If the system is considered unsafe with respect to one or more potential simulated outages, additional control actions have to be taken.

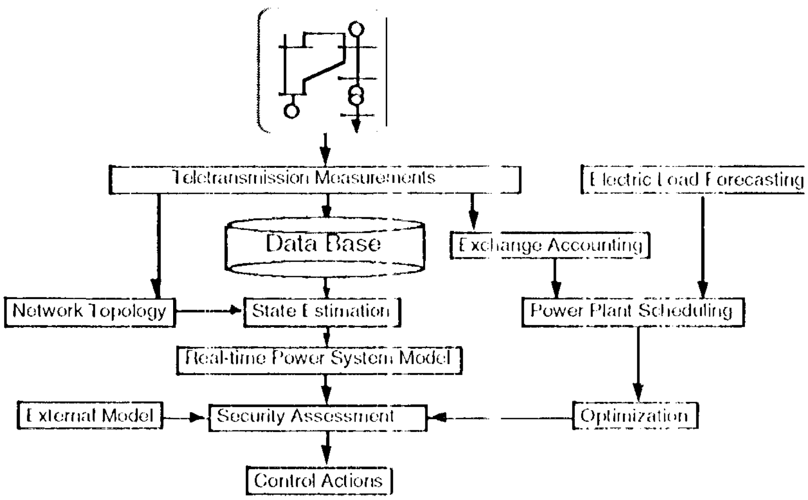

Figure 1: Power System Planning, Operation and Control

Chapter 2 ANN for Power Systems: Motivation

A reliable, continuous supply of electric energy is essential for the functioning of today's complex societies. Power system outages leading to a partial or complete breakdown of the system, although rare events, are extremely expensive. For example in July 1977, such a blackout occurred in the State of New York as a consequence of two lightning strokes, equipment failure and human error. It left the City of New York without power for several hours and resulted in economic losses in the order of 350 Million US$, [Wilson and Zarakas, 1978].

Due to a combination of increasing energy consumption and impediments of various kind to the extension of existing electric transmission networks, these power systems are operated closer and closer to their limits. This situation requires a significantly less conservative power system operation and control regime which, in turn, is possible only by monitoring the system state in much more detail than was necessary previously.

Fortunately, the large quantity of information required can be provided in many cases through recent advances in telecommunications and computing techniques. There is, however, a lack in evaluation techniques required to extract the salient information and to use it for higher-order processing. Whilst the sheer quantity of available information is always a problem, this situation is aggravated in emergency situations when rapid decisions are required.

Because the behavior of power systems is highly non-linear, its monitoring and control involves several hundred variables. Non-linear load demands and dynamic loads are difficult to model.

These problems provide an important motivation to explore novel data processing techniques like artificial neural networks (ANN). These have proven their potential in the area of prediction, approximation, classification and control of non-linear systems.

Early projects explored simple ANN based machine-learning techniques for load forecasting [Dillon *et al*, 1975] and transient stability [Saito *et al.*, 1975] already in the 70's. With the emergence of more powerful computers ANN gained renewed interest from 1988 on, when Sobajic *et al.*, [1988] and Aggoune *et al.*, [1989] assessed their potential for transient stability and static security assessment. These projects have led to a sudden upsurge in applying neural net approaches to a number of power system problems. This work has been documented in more than 400 publications.

In the following chapter, an evaluation of the current state of the art of this research and development activity is provided. This assessment is based on a review of more than 200 different projects published before April 1995. A tutorial introduction to ANN applications in power systems and the reference list for the reviewed papers can be found in Dillon and Niebur [1995]. A bibliographical survey covering 1988-1993 world-wide is presented in the paper issued by the CIGRE Task Force on Artificial Neural Net Applications in Power Systems, [CIGRE, 1993].

Chapter 3 ANN for Power Systems: State of the Art

ANN application areas in power systems

Figure 2 shows the different power system areas where ANN approaches have been investigated. In the figure, the absolute number of projects in the different areas are shown in parenthesis. Time-series prediction in the area of Load Forecasting has turned out to be the most promising area of ANN applications. It was mainly motivated by the lack of automated tools in the utilities and the expected economical gain. Research in other major application areas like security assessment attempts to exploit the data reduction and classification capabilities of ANN in combination with conventional simulation techniques. The potential of ANNs for non-linear adaptive filtering and control stimulated research in the area of control of highly non-liner power system behavior.

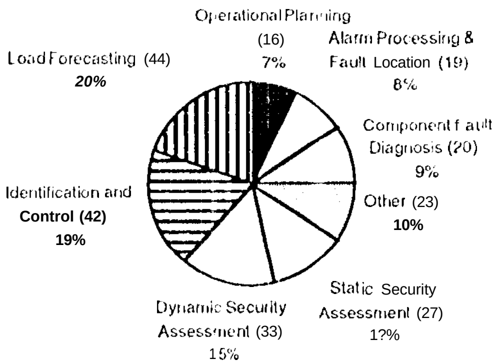

Figure 2 Artificial Neural Net Applications in Power Systems; A Review of 224 Projects

As indicated in figure 3, for power systems, the most frequently applied artificial neural net type is the multi-layer perceptron. Note that the percentage displayed by the different bars refers to the absolute number of projects shown in parenthesis.

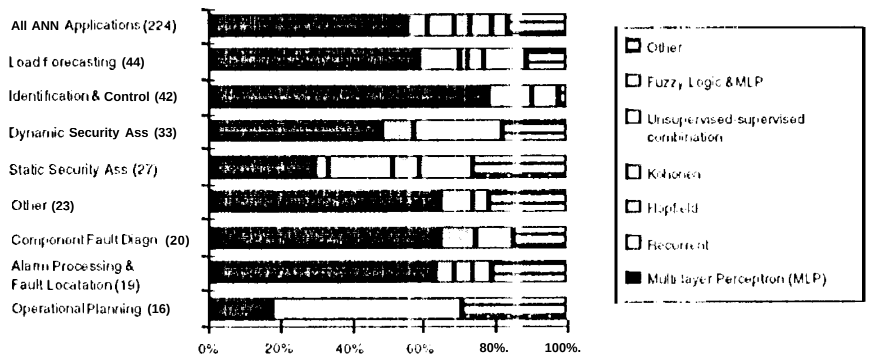

Figure 3 Artificial Neural Net Types Used in Power Systems; A Review of 224 Projects

ANN models used in power systems

The **multi-layer perceptron** (MLP) computes a non-linear approximation of the underlying function specified by the training patterns (x^{μ}, y^{μ}_{target}). The MLP is probably the best investigated ANN model. It is used in nearly every area of power systems whose task can be formulated as an approximation problem. For example in the area of load forecasting the MLP is used for the prediction (approximation or non-linear regression) of the hourly load as a function of the load of the previous 24 hours. As a classifier (approximation of the Boolean function secure/insecure) it is applied in power system security assessment. The MLP can also be viewed as an associative memory where an input vector is associated with an output vector. This formulation is used in some unit commitment and alarm handling applications. The MLP is often used in combination with **Fuzzy Logic** Techniques where qualitative attributes like safe or unsafe are first translated into numbers. The MLP is then used as a regression tool in order to estimate additional parameters. A generalization of MLPs, **dynamically recurrent nets** emerge as promising tools for adaptive prediction in the area of load forecasting, identification and control.

The **Kohonen map** quantifies the input space, i.e. it divides the input space into a certain number of classes and constructs a typical presentation (code vector) for each class. In the area of power system security assessment the self-organizing feature map is used in order to reduce the space of all feasible operating points into a finite set of typical operating points. In the area of load forecasting the self-organizing feature map creates classes of load patterns for example corresponding to classes of days and seasons. The Kohonen map or other unsupervised ANNs are often used in **combination** with supervised approaches or conventional tools. The unsupervised net serves as a pre-processing tool for data reduction, the supervised net estimates associated parameters like peak load or security class.

In the power systems area the **Hopfield net** is mainly used as an optimizer as for example for state estimation, optimal load flow, unit commitment and economic dispatch. Due to the large number of local minima (spurious states) of the Hopfield energy function, the Hopfield net usually computes only a local optimum. This sub-optimal solution however can be obtained very fast. The sub-optimum often serves as a initial value for other optimization techniques like dynamic programming which are slower in performance but better in accuracy.

Academic and industrial participation and development states of ANN projects

As indicated in Figure 4, 60% of all ANN projects are pursued in academic research laboratories without industrial participation. This is not necessarily due to lack of interest from industry. 110WCVQJ some application areas like load forecasting and fault diagnosis rely heavily on measured real-world data usually only available from a manufacturer or a utility. In other areas, like security assessment or operational planning, data can be obtained through simulation and standard model data. Although desirable, the collaboration with industrial partners is therefore not mandatory for feasibility studies.

Load Forecasting and Component Fault Diagnosis testing can further be conducted off-line without time constraints and without direct coupling with power system data acquisition, operation and control. Possible errors are therefore less salient and can be checked by experienced engineers without time pressure. Because of these considerations load forecasting and fault diagnosis are the most mature application areas.

On the other hand, for power system control, the control tool, whether conventional or ANN has to be operated on-line. Its reaction time is extremely limited and control errors can easily lead to a break down a substantial portion of the interconnected system. Therefore power system control is still done in the most conservative manner. In critical situations, it is the practice of some experienced operators to even remove conventional controllers like Power System Stabilizers. New control tools need to be extensively tested before they can be integrated into the existing complex power system. This process takes time. Field tests for control have however been reported for isolated components like a photovoltaic storage, [Hiyama *et al.*, 1995].

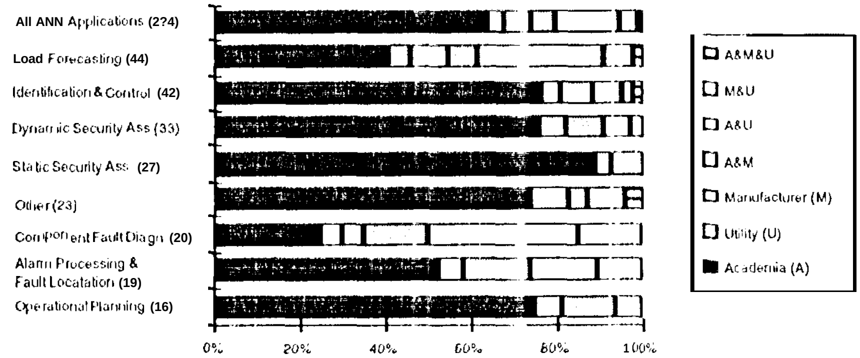

Figure 4 Industrial Participation in the Development of ANN Applications in Power Systems.

Similar remarks apply to the area of security assessment. Further in both areas data covering significant periods of operation are not readily available and have to be collected for the specific ANN applications.

In addition to load forecasting and fault diagnosis, alarm processing and fault location are also reaching field test and operational stages, see figure 5. Unfortunately industrial research projects are often published at the feasibility stage only. Operational systems are rarely discussed in detail. Therefore some of the publications cited below do not report on the final project stage.

For the classification of projects, four cases have been distinguished: ANN applications using model data, that is either standard test data, simulated data or a small subset of real world data which can only qualify for a feasibility study; ANN using real world data with the ANN implementation running in a non-industrial environment; ANN applications subjected to field tests in an industrial environment; ANN applications already in operation in a power system utility. Note, that some field tests run in a utility may have a smaller scope or a prototype character than some of the full scale implementations running in academic environment.

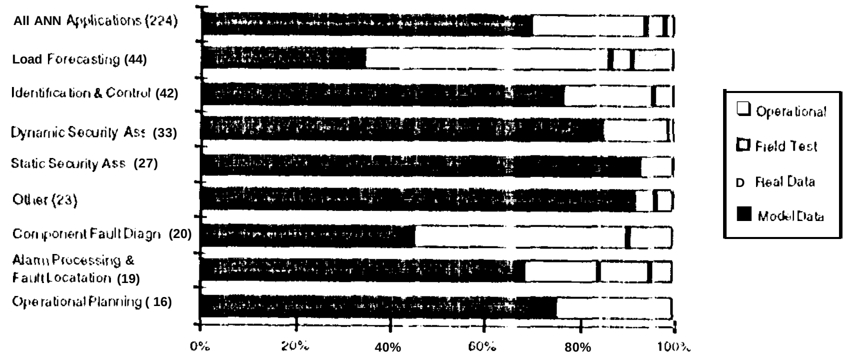

Figure 5 Development State of ANN Applications for Power Systems as of April 95.

Operational systems have been reported in the area of load forecasting by the following utilities and manufacturers: Utility of Western Bohemia, Czech Republic [Böhm *et al*, 1994], Pacific Gas & Electric, USA, [Papalexopoulos *et al.*, 1994], ENEL, Italy, [Sforna, 1995] ELSAMPROJECT, Denmark, [Kristgeirisson, 1995], Electric Power Research Institute (EPRI), USA, a research agency funded by American utilities, [Khotanzad, *et al.*, 1995]. Field test have been reported by: ABB and EOS, Switzerland, [Piras, 1995], Siemens, Austria and Bayernwerke AG, [Baumann *et al.*, 1993] and Tractebel, [de Viron, *et al.*, 1993].

In the area of alarm processing and fault location, operational systems have been reported by the Indian Institute of Science, Bangalore, India [Swarup and Chandrasekharaiah, 1991] and Hitachi, Japan, [Kanoh *et al.*, 1993]. Field tests are reported by the University of Dortmund, [Handschin *et al.* , 1994] and Itaipu, Brazil, [Alves da Silva *et al.*, 1994]. Field tests for component fault diagnosis have been conducted by Southern California Edison, [El-Sharkawi *et al.*, 1994]. Factory tests were conducted by Mitsubishi, Japan. Finally, in the area of control field test are reported by BC Hydro, Canada [Neilly *et al.*, 1991] and Sanyo Electric, Japan, [Hiyama *et al.*, 1995]. For fast dynamic security monitoring in a medium scale network with Diesel and wind power production; a pilot installation is running successfully in the island of Lemnos - Greece [Peças-Lopez *et al.*, 1994].

Chapter 4 Conclusion

This paper studies artificial neural net applications for power systems based on a world-wide literature review. Project development is discussed under technical and practical aspects. Seven years after the first publication in the area of ANN applications for power system planning, operation and control, several systems are now either tested or fully operational in utility control centers. They have left the idea state and are becoming a more market-oriented application. After having been promoted as being capable of solving any problem and after being blamed for promising too much, artificial neural nets are finally being tested in a real-world environment, the power system control center.

However there remain some major challenges to be tackled before ANN can find their place in daily operation in a control center:

1) With the exception of load forecasting, the majority of reviewed papers report on work on small-scale test systems. A major research effort is still necessary to prove the effectiveness of these tools for real world systems. The high dimensionality of input vectors and consequently the large size of the training set can lead to an unreasonable amount of CPU time requirement for the simulated ANN even in the off-line learning phase. Hierarchical ANNs for groups of cases as proposed for fault diagnosis or contingency analysis present a partial remedy.

2 The retraining or updating of the ANN in the case of power system changes has to be investigated especially for those applications with large training time. This point is also crucial for systems where the training set is obtained either by time-consuming off-line power systems simulations (transient stability) or by rarely occurring real-world data (fault detection).

3) The integration of the new technology, either an ANN simulator or future ANN hardware into the existing EMS has not been addressed up to now. This includes technical aspects as well as user acceptance.

Hybrid approaches, that is a combination of ANN with another tool are an emerging area of research. Since ANNs can be viewed as "low level" data processing tools, symbolic reasoning using fuzzy logic and expert system techniques are suggested for adjustment and interpretation of ANN results. For additional references see CIGRE, 1993.

Acknowledgment

I am thankful to my colleagues of CIGRE Task Force 38-06-06 on Artificial Neural Network Applications for Power Systems set up by CIGRE (Conference Internationale des Grands Réseaux Electriques) for valuable inputs and discussions.

The work reported in this paper was started at the Swiss Federal Institute of Technology, Lausanne (EPFL), sponsored by EPFL, and was completed at the Jet Propulsion Laboratory, California Institute of Technology, sponsored by the U.S. Department of Energy through an agreement with the National Aeronautics and Space Administration.

Reference herein to any commercial product, process, or service by trade name, trademark, manufacturer, or otherwise, does not constitute or imply its endorsement by the United States Government or the Jet Propulsion Laboratory, California Institute of Technology.

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